# HARMONIZING EMOTION: A MULTIMODAL APPROACH TO ANALYZING HUMAN AFFECT IN MUSIC RECOMMENDATION SYSTEMS

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#### Abstract:

Music is a worldwide language that everyone throughout the world enjoys. Zatorre and Peretz (2001) state that, musical undertakings with their unique essence appear to have been a part of every recorded society on Earth, dating back at least 250,000 years [1]. As the digital age advances, Customized music suggestion systems are now deeply ingrained in our everyday routines, providing us with a curate's selection of songs that match our preferencesMudit Kumar Tyagi et.al [2]suggested a method for extracting user preferences based on their music listening history. Incorporating demographic information such as age and gender provides a more nuanced understanding of a listener's identity. People of different ages and genders may have unique musical preferences, and these attributes can act as significant filters in the recommendation process. For example, a teenager's taste in music is likely to differ from that of a middle-aged adult. Similarly, gender can play a role in shaping musical choices. Integrating age and gender detection into music recommendation systems ensures that the music offered is not only personally relevant but also age-appropriate and respectful of gender sensitivities. This research proposes a multimodal approach, combining demographic human features and emotional signals, to refine and personalize music selection through advanced machine learning techniques.

Keywords: Music recommendation, Multimodal approach, demographic features

### Introduction

The impact of music on human behavior is multifaceted. Studies indicate music significantly influences emotions, spanning joy, excitement, sadness, and nostalgia. Music therapy is employed clinically to address anxiety, depression, and stress, enhancing emotional well-being. Music shapes and reflects cultural identity, influencing social norms and values. Physiologically, music impacts heart rate, blood pressure, and cortical levels.

Personalized traditional music recommendation systems aim to provide users with music suggestions tailored to their individual preferences. Various approaches and algorithms such as



Collaborative Filtering,Content-Based Filtering,Hybrid Systems,Matrix Factorization,Deep Learning Models,Knowledge-Based Systems,Context-Aware Recommendation,and Implicit Feedback Models are used individually or in combination depending upon available data, system goals, and the desired level of personalization.

From the various mentioned approaches there are three main approaches to customize music recommendations: collaborative filtering (CF) [3], content-based (CB) [4], and hybrid [5]. Based on the songs that users have listened to in the past, CB suggestions present similar songs to them. CF recommendations make music recommendations to users based on an analysis of the listening preferences of people with similar tastes. The hybrid method combines the insights from both the CF and CB methodologies to provide personalized music recommendations. Following table compares the three approaches in music recommendation system

Music Recommender System	Data Working Source	Technology Used	Website
Content Based Recommendation	Uses the user's historical data and takes into account the audio's inherent characteristics.	Gaussian Mixture Models (GMM) & Word Frequency Mining (WFM)	Shrimps Music
Collaborative Filtering Recommendation	Consider the users rating for a particular music.	Association Rule, KNN, Clustering, DecisionTree, Regression, CNN	Last FM music station
Hybrid Approach Recommendation	Combinestheapproachesofdifferentmusicrecommendationsystems	CombinationofcontentandcollaborationTechniques	7HCCMR

### Table 1: Summary of different approaches for Music Recommendation System

Demographic features, such as age, gender, and emotion can be valuable in understanding and enhancing personalized music recommendations.Considerable research has utilized deep learning techniques like Convolutional Neural Networks (CNN) and Artificial Neural Networks (ANN) for age, gender estimation, and emotion detection. Within CNN, Feature extraction identifies age, gender, and emotion-related features. Additionally, Feature classification in CNN categorizes facial images accurately into age groups, genders, and emotions such as happiness, sadness, anger, and neutrality.



The music recommendation problem can be divided into two sub problems first is Forecasting i.e predicting the likely music for a user and second is recommending or suggesting the list of probable music, the user loves to listen.

**Forecast:** Let  $I = \{i_1, i_2, i_n\}$  be the set of all possible items that can be recommended (a goal music collection), and let  $U = \{u_1, u_2, ..., u_m\}$  be the set of all users. Every user interface demonstrated interest in a certain set of goods.  $Iu_i \subseteq I$ .

**Suggestion:** Calculate the function  $P_{ua}$ ,  $_{ij,an}$  anticipated preference which denotes that itemij $\notin I_{ua}$  for the active user  $u_a$ 

### **Literature Review:**

Research in various areas is made to detect age, gender and emotions of the people. While some of the researchers took audio, others used image capture to extract features before conducting analysis. The following table depicts the summary for publication papers related to age, gender & emotion detection systems.



Paper No	Objectives	Method Used	Findings
Faper No         [6] (2023),         [7] (2022),         [8](2020),         [9](2020).	The main focus of the article is on using facial photos to assess age, gender, and emotions in real time.	<ul> <li>Method Used</li> <li>The HOG-Viola- Jones algorithm demonstrates</li> <li>high accuracy in age, gender, and emotion recognition.</li> <li>•Recognition</li> <li>•Recognition</li> <li>tasks employed</li> <li>CNN along with algorithms such as AdaBoost,</li> <li>PCA, HOG, LBP,</li> <li>HAAR, FPLBP,</li> <li>and LDA.</li> </ul>	<ul> <li>A complete survey of techniques for age, gender, and emotion classification was reviewed</li> <li>The Viola- Jones algorithm serves for object detection and face detection purposes.</li> <li>Local Binary Pattern (LBP) finds application in texture classification and real-time image</li> </ul>
			anary 515.



[11](2020)paper compares nineutilized methods encompassNaive outperforms Rame outperforms Rame Forest and Deci Iearning[12](2016)conventional learningComplement Naive Bayes, methods for mood detection.Forest and Deci mood variations.[12](2016)conventional learningComplement Random Forest, and classifiers.Forest and Deci mood variations.[12](2016)methods for methods for mood detection.Random Forest, Decision Tree, and classifiers.mood variations.[12](2016)Mood classifiers'Decision Tree, and classifiers.• Simple classifiers can used for study mood patterns[11](2020)Mood classifiers'• Gaussian individuals.• Simple classifiers can used for study mood patterns[11](2020)Twitter data pertaining to COVID-19.• Binary classifiers were classifying text based	[10](2022)	• The	• The	• Complement
[12](2016)conventional learningComplement NaiveForest and Deci Tree in detect mood variations.methods methods detection.Random Forest, Decision and classifiers.Tree in detect mood variations.Mood classifiers'Decision and classifiers, efficacy efficacy treeSimple classifiers, mood patterns individuals.Mood classifiers'• Gaussian classifiers, Multi- mood patterns individuals.• Simple classifiers can used for study mood patterns individuals.Twitter COVID-19.based, were employed.• Binary studiedSystemclassifiers were classifiers wereclassifying text based	[11](2020)	paper compares nine	utilized methods encompass	NaiveBayesoutperformsRandom
recommends adapted for on moods. songs based on multi-class user's mood and categorizations. preferences	[11](2020) [12](2016)	nine conventional learning methods for mood detection. Mood classifiers' efficacy is evaluated using Twitter data pertaining to COVID-19. System recommends songs based on user's mood and preferences	encompass Complement Naive Bayes, Random Forest, Decision Tree, and classifiers. • Gaussian classifiers ,Multi- class and rule- based, Bayesian were employed. • Binary classifiers were adapted for multi-class categorizations.	outperforms Random Forest and Decision Tree in detecting mood variations. • Simple classifiers can be used for studying mood patterns in individuals. • Deep learning algorithms can be studied for classifying text based on moods.



[13](2020) [14](2010) [15](2018)	<ul> <li>The aim of the paper is to detect emotions in real-time using webcam images.</li> <li>Features are extracted from facial landmarks for emotion detection.</li> </ul>	ReLU(Rectified Linear Unit), CNN(Convolutio nal Neural Network), Max-Pooling Circular Local Binary Pattern, KNN(K-Nearest Neighbors) Logistic Regression	<ul> <li>Proposed model predicts sentiment based on video information.</li> <li>Resulting output can be used to address mental disorders and stress.</li> </ul>
[2](2014)	Music Information Retrieval (MIR) was designed using two case	Recognition Feature Extraction Two case studies, Emotify and Hooked, were established for gathering data in	<ul> <li>Collecting data through online multiplayer games for</li> </ul>
	studies	the field of Music Information Retrieval (MIR). Emotify specializes in emotional annotation of music. Hooked explores musical catchiness.	<ul> <li>music</li> <li>research.</li> <li>Developing games to annotate music</li> <li>emotionally and investigating musical catchiness.</li> </ul>



[17](2015)	The voice-based	Principal	The system discerns
	speaker	component	the age and emotions
	processing	analysis (PCA ),	of speakers,
	system is investigating speaker attributes such as age and emotions (including stress and mood), which may vary depending on	Meel frequency cepstral coefficients (MFCCs),Gaussi an mixture model (GMM)	considering gender differences. The proposed system aims to enhance human-computer interaction.
	gender.		
[18](2020)	To achieve the highest in accuracy in predicting emotions among individuals experiencing depression.	Meel frequency cepstral coefficients (MFCC), Multi- layer Perceptron classifier (MLPC)	The framework preprocesses the audio data and identifies emotions using the MLP classifier.



		~ ~ ~	
[19](2014)	Introduces a	Support Vector	The system is
	system capable	Machine (SVM)	composed of
	of discerning an	classifiers ,Pitch	two
	individual's	Frequency	subsystems:
	emotional state	Estimation	1)
	from recorded	method	
	audio signals.		emotion
	_		recognition
			(ER)
			2) gender
			2) gender
			(CP)
			(OK)
			The
			experimental
			findings
			underscore
			that
			integrating
			the Gender
			Recognition
			(GR)
			(UK)
			subsystem onhonoog the
			ennances the
			overall
			accuracy of
			emotion
			recognition
			trom 77.4%
			to 81.5%.

Table 2: Summary for age, gender and emotion recognition

### **Proposed System**

The proposed system can identify emotions more accurately by combining information from multiple modalities, including text analysis, speech tonality, and facial expressions. When combined, the distinct insights from each modality can provide a more thorough picture of the user's emotional state. The accuracy, resilience, and user experience of the system can be greatly improved by using a multimodal approach to emotion recognition and music selection. This will result in interactions that are more engaging, natural, and sympathetic.





### Fig 1: Proposed System Architecture Diagram

The Proposed system can be explained using following terms:

**Multimodal Approach:** A multimodal approach involves combining information from multiple modes or modalities to enhance understanding, representation, or interaction in a system. The study encompasses the collection of diverse user data such as age ,gender along with emotional signals captured using multiple modalities, such as facial expressions, physiological responses, and user-provided emotional labels this data can be audio ,video or text.

#### **Dataset creation:**

The image, gender and emotion dataset will be collected from IMDB-WIKI Dataset, LFW (Labeled Faces in the Wild) Dataset, AffectNet Dataset. After working on these three datasets some real time images of people with different ages, gender and various facial expressions will be collected.

### Age Detection:

Machine learning and deep learning models will be utilized for age detection. Common deep learning architectures such as Convolution Neural Networks (CNNs) or recurrent networks can be utilized for detecting age from both image and voice data. A deep learning architecture called a convolution neural network (CNN) is made to learn straight from data. It is a kind of artificial neural network that is widely used for object and picture categorization and recognition. Deep Learning is able to recognize things in photos by using CNNs. These networks are essential for many applications, including speech recognition in natural language processing, video analysis,



obstacle recognition in autonomous cars, image processing, and computer vision tasks like segmentation and localization.

In a CNN, the input layer receives image pixels arranged in arrays. Multiple hidden layers within CNNs engage in feature extraction from the image through various operations such as convolution, pooling, rectified linear units, and fully connected layers. The convolution layer initiates the feature extraction process from the input image. Finally, the fully connected layer categorizes and identifies the object, producing the output layer.

### Gender and Emotion Detection:

Machine learning models, such as deep learning models like CNNs or Support Vector Machines (SVM) for gender detection from audio and visual data is widely used. For Emotion Detection CNNs for facial expression analysis.

### Music recommendation algorithms:

After identification of the age, gender along with emotions such as happiness, surprise, anger, neutrality, and sadness The system provides a curates playlist of music that matches the detected mood and the other parameters. Algorithms like collaborative filtering, content-based filtering, and hybrid methods, take into account the user's age, gender, and emotional state to generate personalized music recommendations.

### Providing user privacy & Feedback Mechanism:

Implement strict privacy protection mechanisms to safeguard user data of captured image used to detect gender, age, and emotion as this data can be sensitive. The captured image can be encrypted Discrete Parametric Cosine Transform (DPCT) algorithm. The 2D DPCT, a sophisticated cosine transform, necessitates 12 parameters, posing challenges in real-world applications. Nonetheless, these parameters enhance the potency of the 2D DPCT, furnishing it with robust characteristics.

### Summary :

This review study delves into the nascent domain of multimodal techniques in music recommendation systems, emphasizing three crucial demographic aspects: age, gender, and emotion. It compiles recent findings and approaches that use several modalities, including user listening history, lyrics, audio content analysis, and contextual information from social media. Accurately recognizing gender, emotional state, and age group through these multimodal methodologies presents both potential and challenges; advances in machine learning algorithms and feature extraction techniques are highlighted. It also looks at the effects of using this kind of demographic data in music recommendation algorithms, such as better user experiences and customized playlists. All things considered, the research highlights how multimodal methods can be used to customize music recommendations based on complex demographic preferences, opening the door to more advanced and user-focused music recommendation systems.



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